Volatility, Liquidity, and Liquidity Risk[*]

Dan Amiram[†]   Balazs Cserna[‡]   Ariel Levy[§]

This Draft: December 15, 2016
First Draft: February 17, 2015

Abstract

Liquidity affects various capital market outcomes such as expected returns and capital structure. Prior research has shown that an important determinant of liquidity is volatility, where higher stock return volatility is associated with higher illiquidity. Using recent developments in the literature, we revisit this relation and decompose total volatility into its jump and diffusive components and argue that the two volatility components are predicted to have opposite effects on liquidity. This decomposition is motivated by the fact that variation in the structure of volatility across firms is driven by variation in information environments. Therefore this decomposition gives rise to a new unexplored channel, independent of information asymmetry and total volatility, through which the information environment can shape liquidity. We find a positive relation between the jump component of volatility and illiquidity that is independent of any information asymmetry effects. In contrast, we find a negative relation between diffusive volatility and illiquidity. Finally, we show that these findings translate to differential effects on liquidity risk and premium for the jump and diffusive volatility components. Our findings have implications for the understanding of asset prices, corporate finance decisions and policy-makers.

1   Introduction

Stock liquidity and its variation affect a number of capital market outcomes such as expected returns (e.g., Amihud and Mendelson, 1986 and 2015; Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005), capital structure (e.g., Lipson and Mortal, 2009), dividend policy (Banerjee et al., 2007), and ownership structure (e.g., Bhide, 1993). Given these important implications, numerous theoretical and empirical studies have investigated the determinants of liquidity and demonstrated the role stock return volatility plays in driving illiquidity (e.g., Stoll, 1978a; Stoll 1978b; Stoll 2000; Amihud and Mendelson, 1989; Bao and Pan, 2013).

However, treating volatility as a uniform measure with a homogeneous impact on liquidity overlooks the subtle, yet potentially important, structure of total volatility. More recent developments in the asset pricing literature treat stock returns as a jump-diffusion process, that is, as a combination of a continuous Brownian motion component and a discontinuous jump component. Consequently, this approach implies that the total return variance is an aggregate outcome of two separate sources that have very different characteristics. While volatility patterns generated by a discontinuous jump process arise from infrequent, large, isolated price changes, the diffusive volatility arises from smooth, continuous, small price changes. The overall volatility is merely the integration of these two types of volatility. Importantly, as discussed in more detail below, each volatility component is expected to have an opposite relation with liquidity.

The decomposition of total volatility into its jump and diffusive components is not a mere "technical" exercise, but is motivated by an important economic reasoning. Each volatility component is driven by different economic forces related to the rate of information arrival. Stocks for which information flows in a smoother and more continuous way are more likely to be governed by a diffusive process. On the other hand, stocks for which information arrives in a bulky, discontinuous way are more likely to be subject to jumps (e.g., Maheu and Mc-Curdy, 2004). Therefore, firms with identical volatility can have very different composition of volatility components depending on the rate of information arrival. The rate of information arrival for each firm is determined by its information environment which is governed by various factors, such as the disclosure regulations that apply to it, its voluntary disclosure policy, and its level of analysts coverage.[1]

---

[1] In a companion study we confirm this intuition by showing that issuing management forecasts, increasing their number, and having greater analyst coverage all reduce jump volatility. Moreover, following Kelly and Ljungqvist (2012), we use drops in analyst coverage as a result of an exogenous brokerage house closures to show that a reduction in analyst coverage causally increases jump volatility. We show that the effects of information environment on jump volatility that we document remain after controlling for information

Relating the firm's information environment to capital market outcomes has been a central theme in the literature that examines the role of information in capital markets. Numerous studies in accounting and finance emphasized its importance to liquidity and liquidity driven outcomes (e.g., Kelly and Ljungqvist, 2012; Balakrishnan, Billings, Kelly, and Ljungqvist, 2014). However, the information environment can give rise to multiple channels that shape liquidity, where the existing literature has so far focused on the channels of information asymmetry and total volatility.

We emphasize a new unexplored channel through which the information environment can shape liquidity and liquidity driven expected returns. We highlight that the information environment also works through the structure of volatility to shape liquidity and liquidity driven outcomes, independently of the already explored channels of information asymmetry and total volatility. The information environment determines the pace at which information arrives to the market and, consequently, affects the relative dominance of the jump versus the diffusive component of volatility. Hence, as we argue in this paper, since each volatility component impacts liquidity differently, firms with different information environments are likely to have different levels of liquidity. That is, even in the absence of any differences in information asymmetry or total volatility across firms, differences in their information environments can still affect liquidity differently through their effect on the structure of volatility.[2] Moreover, this channel implies that differences in information environments create differences in liquidity even in the absence of any information asymmetry at all.

The literature on jumps has highlighted two facts that lead to differential predictions for each volatility component on liquidity. These facts are directly linked to the theory of liquidity, which emphasizes the risks market makers face in determining liquidity and particularly inventory risk. The first fact is that jumps in prices are difficult to hedge, unlike diffusive changes (e.g., Garleanu et al., 2009). Market-makers bear the risk of price changes to their stock inventories, which they must maintain. Therefore, bid- ask spreads are set to compensate them for bearing this inventory risk (e.g., Stoll 1978a; Amihud and Mendelson, 1980; Ho and Stoll, 1981; Ho and Stoll, 1983). In a diffusive environment market-makers can control their potential losses, update their inventory portfolios, and fix "stop-loss" rules in a more flexible and gradual manner compared to a trading environment that exhibits infrequent

asymmetry. The results of the companion study are replicated in the sample of the current study and provided in Appendix A, Panels A and B.

[2]In this study we do not aim to empirically establish a causal link between information environment, jump volatility, liquidity and liquidity risk. We take the more modest goal of being the first to document these associations. Any use of causal terms throughout the paper is motivated only by the theoretical arguments stated in the introduction and should not be related to in the strict econometric sense.

dramatic price changes. That is, jumps impose a more restrictive set of risk management tools and stopping rules compared to diffusive price changes.[3]

Similarly, to reduce inventory risk, market-makers often hedge their inventories with correlated instruments, such as options and other correlated stocks or ETFs. Therefore, it is mainly the non-hedgeable portion of their inventory that drives their compensation in the form of bid-ask spreads (e.g., Benston and Hagerman 1974; Ho and Stoll, 1983; Froot and Stein 1998; Naik and Yadav, 2003a; Naik and Yadav, 2003b). Jump risk, as a discontinuous price change, cannot be easily hedged away, as dynamic replicating strategies become infeasible under incomplete markets (e.g., Garleanu et al., 2009; Jameson and Wilhelm, 1992; Gromb and Vayanos, 2002; Chen et al., 2014). Therefore, as the non-hedgeable portion of total volatility, it is the jump-driven component that market-makers are likely to demand compensation for.

The second fact is that diffusive volatility is associated with increased trading, while jump volatility is not (e.g., Giot et al., 2010). Higher turnover rates reduce market-makers' inventory costs as they can match the order flow much more easily and consequently increase liquidity (E.g., Tinic and West, 1972; Stoll, 1978a). This line of reasoning entails a negative association between diffusive volatility and illiquidity through turnover.

Taken together, these reasons suggest a positive relation between jump volatility and illiquidity, while a negative one is expected between diffusive volatility and illiquidity.[4]

To address these predictions, we follow standard methodologies implemented and validated by Ait-Sahalia (2004) and others to fit a log-normal jump-diffusion process to all stocks listed on the NYSE and NASDAQ from 2002-2011. We estimate the parameters of the jump and diffusive processes, measure total return variance, and disentangle the respective contribution of the jump and diffusive volatility components to total variance. As Ait-Sahalia (2004) points out, this methodology can perfectly disentangle the diffusive and jump components. Then, using Fama-MacBeth regressions we test for the potential impact each class of volatility has on bid-ask spreads.[5]

---

[3]See Longstaff (1995, 2014), who models the implications of a similar aspect to illiquidity.

[4]Prior literature emphasized that crash risk and jump risk are inherently different theoretical constructs. Our reasonings focus on additional differences between jump risk and crash risk in a liquidity setting. Market makers' inability to successfully hedge or risk-manage their inventory exposes them to risks of price changes in both directions, as their inventory is long and short, and not just downside risk. Also, these risks exist for price changes that are not extremely dramatic as in "crashes", yet are still discontinuous jumps. Nevertheless, in Section 5.3 we validate empirically that crash risk has little effect on our results.

[5]Inferences throughout this paper remained qualitatively the same when we used the Amihud (2004) illiquidity measure instead of bid-ask spreads.

We find that the positive relation between volatility and bid-ask spreads is exclusively driven by the jump component, as we find a strong positive relation between the jump component and bid-ask spreads. In contrast, we show that the diffusive component is negatively associated with bid-ask spreads. Supporting our theory we also show that the negative association between diffusive volatility and illiquidity is driven by the relation between diffusive volatility and turnover. These results are independent of any information asymmetry effects as they are maintained in all levels of information asymmetry and remain robust to the inclusion of a proxy for information asymmetry as a control variable. Gauging the economic magnitude of their effects, an increase of one standard deviation in the jump-driven volatility component increases bid-ask spreads by approximately 30 basis points, whereas an equivalent increase in the diffusive volatility component decreases bid-ask spreads by approximately 10 basis points. Finally, we show that our results are unlikely to be driven by reverse causality. Since our findings are maintained at all levels of turnover, it is unlikely that merely thin trading fully drives our findings.

One possible implication of the differential results that each liquidity component has on liquidity, is that it may also carry over to liquidity risk and liquidity risk premiums. A number of studies (e.g., Pastor and Stambaugh, 2003; Sadka, 2006) have shown that liquidity risk is priced. These studies show how stock liquidity is sensitive to aggregate market liquidity and market performance. Therefore, investors demand higher risk premiums for stocks that suffer from greater illiquidity in times of stress, times in which they also exhibit large losses in wealth. In the context of our analysis, since the jump-volatility component is the dominant driver behind illiquidity, it is possible it would also be the main driver determining liquidity risk and liquidity risk premiums.

We find that the jump volatility component has a positive and statistically significant effect for various measures of liquidity risk. On the other hand, the diffusive component has a negative effect on liquidity risk. That is, only jump volatility increases liquidity risk while diffusive volatility does not. Furthermore, following the methodology of Pastor and Stambaugh (2003), we show that only the jump volatility component increases the priced liquidity risk.

Our study contributes to several streams of literature. First, our study contributes to the understanding of the economic forces behind illiquidity. Although prior literature emphasized the importance of information environment to liquidity (e.g., Kelly and Ljungqvist, 2012; Balakrishnan et al., 2014; Amir and Levi, 2016), we are the first to document its effect through the structure of volatility. Relatedly, our findings suggest that firms can improve their liquidity and cost of capital if they are able to enhance their information environment

in a way that reduces jump volatility.[6] Second, our study contributes to the literature that studies the determinants of liquidity, particularly that which documents the relation between volatility and liquidity (Stoll, 1978a; Stoll 1978b; Stoll 2000; Amihud and Mendelson, 1989). Our study enhances this literature by being the first to document that the structure of volatility matters for illiquidity in addition to raw levels of volatility. Third, our study contributes to the literature that studies the consequences of jumps to a variety of financial variables. This literature documented that jump and diffusion processes have very different effects on credit risk (e.g., Zhou 2001; Cremers, Driessen and Maenhout 2008), on market beta (e.g., Todorov and Bollerslev 2010; Cremers, Halling and Weinbaum 2015; Bollerslev, Li, and Todorov 2016), and on stock option pricing (e.g., Duffie, Pan and Singleton 2000; Pan 2002; Garleanu, Pederson and Poteshman 2009). Our study adds to this literature by providing evidence that the jump and diffusive components of volatility have very different effects on liquidity. Fourth, our study contributes to the literature on liquidity risk (e.g., Pastor and Stambaugh, 2003) by showing that the jump and diffusive effects on liquidity also carry over to liquidity risk and premiums.

Moreover, our findings also have regulatory implications to security markets. Our results show that implementing accounting policies that encourage more continuous information disclosure may help increase liquidity. These considerations are relevant to reforms currently being implemented to the regulatory environment in the EU. The European Commission recently removed the obligation to publish interim management statements and announced its intention to abolish quarterly financial reports for publicly traded companies, steps that might have important consequences to liquidity. More generally policies that increase the continuous stream of information to the markets (e.g, enhanced media coverage, social media discussions) and price informativeness are likely to improve the diffusion component of volatility and improve liquidity.

The remainder of this paper is organized as follows. In the next section we describe our methodology and empirical approach followed by our data sources and descriptive statistics. Sections 5 describes our results and discusses additional robustness tests. Implications to liquidity risk and premium are addressed in Section 6 and Section 7 concludes.

---

[6]This yields a change in equilibrium as there are likely significant costs for enhancing the information environment.

2 Methodology

2.1 Model Description and Calibration

In our analysis, we follow a standard framework for modeling jump-diffusion processes and apply estimation procedures that were used, validated and empirically tested in numerous studies (e.g., Ait-Sahalia, 2004; Yu, 2007).[7] Following Merton (1976), we assume a continuous trading market for a stock with price S_t at time t, in which there are three sources of uncertainty: a standard Brownian motion W_t, an independent Poisson process of jump events N_t with intensity λ, and a random jump size Z_t which is distributed lognormally with mean α and variance γ^2. The stock return dynamics are described by the following stochastic differential equation:

$$\frac{dS_t}{S_t} = (\mu - \lambda \cdot \kappa) \, dt + \sigma \cdot dW_t + dJ_t \tag{1}$$

where μ and σ are constants, $\kappa \equiv E(Z_t - 1)$ is the expected relative jump of S_t, and $J_t \equiv (Z_t - 1) \cdot N_t$ denotes the compound Poisson process.[8] Following Merton (1976) and Navas (2003), the diffusive and jump components of total return variance can be expressed in terms of the respective process parameters as,

$$\begin{aligned} V^d &= \sigma^2 t \\ V^j &= \lambda \left(\alpha^2 + \gamma^2 \right) t \end{aligned} \tag{2}$$

which allow for easily calculating the values of the variance components. The total return variance is just the summation of these two components,

$$V = V^d + V^j. \tag{3}$$

Applying ML methodologies, we calibrate the model on historical data for stock returns and obtain a vector of parameter estimates $\theta_i^t = \left(\mu_i^t, \sigma_i^t, \lambda_i^t, \alpha_i^t, \gamma_i^t \right)$ for each stock i estimated over

---

[7]The estimation procedures for jump-diffusion processes are standard and can be found, for example, in Rama and Tankov (2003) and Rüschendorf and Woerner (2002). Furthermore, Ait-Sahalia (2004) validated that such maximum likelihood methods can perfectly identify the diffusive and jump components, particularly in the context of the framework we follow here, Merton (1976).

[8]We follow vast prior literature and do not model volatility as a stochastic process as some studies do. Although stochastic volatility makes the model more "realistic" it adds unnecessary complexity at the expense of tractability in the context of the current study. Moreover, simulation analysis reveals that the correlation between our estimated jump and diffusion parameters in a model with stochastic volatility to a model without stochastic volatility is 0.9 and therefore suggests that there is very little benefit for the additional complexity.

period t. Based on θ_i^t, we then calculate $V_{i,t}^d$ and $V_{i,t}^j$, that is, the respective components of the diffusive and jump variance components out of total variance.[9] For a more detailed description of our framework, estimation procedure and their references see Appendix B.

2.2 Empirical Analysis

We estimate Fama-MacBeth regressions to formally test for different influences each type of variance has on liquidity. We first confirm that indeed total volatility has a positive effect on bid-ask spreads in our sample, as previous studies have shown. Therefore we run the following cross-section regression year-by-year

$$Liq_{i,t+1} = \beta_0 + \beta_1 V_{i,t} + \beta_2 \ln(size)_{i,t} + \varepsilon_{i,t} \qquad (4)$$

where the dependent variable $Liq_{i,t+1}$ denotes the relative bid-ask spread (in percent) for stock i in the following year $t+1$.[10] The explanatory variables on the right-hand side include total variance $V_{i,t}$, the log of the market capitalization $\ln(size)_{i,t}$, and an error term $\varepsilon_{i,t}$, all measured for stock i in year t (January 1 to December 31). This cross-section regression is estimated year-by-year, and then time-series averages are calculated for all coefficients, following the Fama-MacBeth method. Therefore this procedure yields a vector of estimates $\beta = \left(\beta_0, ..., \beta_{1+J}\right)$ that characterizes the variables' effect on liquidity.[11]

In the next step, we explicitly include in the model the decomposition of total variance into its jump and diffusion-driven components. Therefore the new specification is

$$Liq_{i,t+1} = \beta_0 + \beta_1 V_{i,t}^d + \beta_2 V_{i,t}^j + \beta_2 \ln(size)_{i,t} + \varepsilon_{i,t} \qquad (5)$$

where the explanatory variables $V_{i,t}^d$ and $V_{i,t}^j$, the diffusion- and jump-driven variance components, respectively, replace the total variance $V_{i,t}$ in Equation (4). Both $V_{i,t}^d$ and $V_{i,t}^j$

---

[9] An alternative valid way to estimate jump parameters is to use option prices (e.g., Yan, 2011; Cremers, Halling and Weinbaum, 2015). However, many stocks do not have available options for trade. Moreover, trading and quotes are very "thin" and illiquid for other stock options. Therefore, to gain a better coverage of the market, and particularly to study liquidity and liquidity risk implications, we chose our methodology.

[10] In our specification we test for lagged effects since for any decision made in year $t+1$ the only information available is from year t. However, in unreported results we repeated all our regressions using contemporaneous variables instead of lagged ones and find the same effects.

[11] The fact that market-makers face high-frequency intra-day inventory risk should not be confused with our use of annual variables. These variables represent firm characteristics that represent jump and diffusive *risks*, not realized jumps or price changes. They represent the likelihood of jumps and diffusive price changes upon which market-makers base their approach to setting bid-ask spreads. As mentioned earlier, these characteristics are indeed estimated using higher frequency data (daily).

are obtained from the ML estimation. All other variables in the new specification remain unchanged.

3   Data

We obtain from CRSP daily stock prices, volume, shares outstanding, and market-capitalization for all stocks listed on the NYSE and NASDAQ between 2002–2011. We start our sample in 2002, as this is the last year of the minimum tick rules, which imposed regulatory constraints on minimum bid-ask spreads and price changes. For these stocks and years, we also obtain TAQ historical data for bid-ask quotes and calculate their average annual percentage spreads. We calculate average annual turnover rates using volume and shares outstanding data for each stock.

In our final sample, we eliminate all firm-years with less than 245 observations per year, and those with bid-ask spreads (percent) that were larger than 50% or negative. We also eliminate securities that did not have data on market capitalization for year t in the CRSP database; this excludes non-stock securities listed on exchanges. We end up with 9,088 different stocks between 2002–2011, and 61,299 stock-year observations.

We calibrate the return-process model specified in Equation (1) for daily returns and obtain for each stock i and year t a vector of parameters $\theta_i^t = \left(\mu_i^t, \sigma_i^t, \lambda_i^t, \alpha_i^t, \gamma_i^t \right)$ that characterizes the jump-diffusion return process. To gauge the consistency of our calibration with the realized historical data, we compare our model-implied daily-return variance (V_i^t as specified in Equation (3)) with the realized daily return-variance, measured over the corresponding year t. We denote the realized variance by $\widetilde{V}_i^t$. For more than 90% of our sample, the ratio $\frac{\widetilde{V}_i^t}{V_i^t}$ falls between 0.8 and 1.2, implying that there was a good fit between our predicted variance and the actual variance, i.e., no more than 20% deviation.

Finalizing our sample, we eliminate all estimates with extreme values, that is, the highest and lowest 1% for all parameters of the vector θ_i^t. We also eliminate all observations that do not satisfy the condition $\frac{\widetilde{V}_i^t}{V_i^t} \in [0.8, 1.2]$.[12] After applying these additional filters, our final sample contains 44,171 stock-years observations. The average jump size α in our sample is 3% (in absolute values), and the average jump frequency λ is 16%. These estimates are comparable to estimates obtained by prior studies (e.g., Todorov and Bollerslev, 2010; Tauchen and Zhou, 2011).

---

[12]This final elimination does not alter the inferences reported in this paper.

4   Descriptive Statistics

Panel A of Table (1) reports overall average and quintile values for total volatility, jump volatility, and diffusive volatility. Average total return volatility across all years and stocks is around 29%. Average values for the diffusive and jump components are of the same order of magnitude, 18% and 20%, respectively, and their medians are around 17%.[13] Their similar orders of magnitude are also maintained throughout their quintile distribution.

Panel B reports quintile breakdown of average bid-ask spreads across our sample. They are around 1.8% on average with a standard deviation of 2.5%. The median bid-ask spread is around 85 basis points.

5   Results

5.1   Univariate Analysis - Sorted Portfolios

As a first step we provide a univariate analysis in a portfolio framework. We explore the impact each volatility component has on illiquidity while controlling for the levels of the other volatility component. In Table (2) Panel A, we sort all stocks in our sample for each year t on their diffusion-driven variance portion V^d and form five equally weighted portfolios. The first quintile portfolio contains stocks with the lowest diffusive volatility component for a given year, and the fifth quintile contains stocks with the highest diffusive volatility component. We denote these portfolios by $d = 1, ..., 5$. Then, for each year t, we further sort each of the five portfolios $d = 1, ..., 5$ on their jump-driven variance component V^j to form additional five equally weighted subportfolios per portfolio rank d. The first quintile subportfolio contains stocks with the lowest V^j and the fifth quintile subportfolio contains stocks with the highest V^j. This way, we create for each year t and diffusive portfolio rank d five subgroups of stocks ranked from 1-5 sorted on V^j. We denote these subportfolios by $d_j = 1, ..., 5$. We then calculate average bid-ask spreads for each subportfilo in year $t + 1$.

As seen in Panel A, going up the ranking in the jump volatility component while holding diffusive volatility levels fixed has a strong positive on bid-ask spreads. This holds true for all levels of diffusive volatility. The difference in means for bid-ask spreads between high- and low-jump volatility portfolios are all positive and range from 164 to 278 basis point, with

---

[13]The jump and diffusive volatility components do not sum up to total volatility for two reasons. First, the equality holds true for variances and not for standard deviations. Additionally, for total standard variations of returns we use realized standard deviations, while for the diffusive and jump components, we use model implied volatilities. These values are close but not identical.

t-statistics ranging from 18.94 to 27.57 indicating high statistical significance. We provide a graphic presentation of these results in Figure 1 Panel A.

In Panel B of Table (2) we repeat the same procedure the other way around. That is, we sort all stocks on the jump variance component V^j and then further sort each jump portfolio $j = 1, ..., 5$ on the diffusive variance component. This way, we create for each year t and jump portfolio rank j five subportfolios ranked from 1–5 sorted on V^d. We denote these subportfolios by $j_d = 1, ..., 5$. We then calculate the average bid-ask spread for each portfolio (in year $t + 1$).

A very different picture arises for this analysis. As seen in Panel B, this time bid-ask spreads decrease when going up the ranking in the diffusive volatility component while controlling for jump volatility levels. Overall the difference in average bid-ask spreads between high diffusive and low diffusive volatility portfolios are all negative and around -65 basis points, with *t*-statistics ranging from -7.76 to -13.10. The only exception is for the highest jump portfolio that exhibits a very small and insignificant difference in bid-ask spreads between its high and low diffusive volatility portfolios. We provide a graphic presentation of these results in Figure 1 Panel B.

5.2 Fama-MacBeth Regressions: Total Volatility and Illiquidity

In the first step, we replicate the results from previous studies to confirm that total volatility has a positive impact on illiquidity in our sample. The first column in Table (3) reports Fama-MacBeth regression results based on the model specified in Equation (4). Total variance indeed has a positive and significant impact on bid-ask spreads, with a coefficient estimate of 2.19 and *t*-statistic of 5.52. Market capitalization also has a negative and statistically significant effect. These findings are consistent with prior studies that found a positive relation between volatility and illiquidity costs (e.g., Stoll, 1978b, 2000; Pastor and Stambaugh, 2003).

5.3 Fama-MacBeth Regressions: Volatility Components and Illiquidity

In the next step, we decompose total volatility into its jump and diffusive driven components. The second column of Table (3) reports Fama-MacBeth regression results for the regression specified in Equation (5), which explicitly models separate effects for each component. The estimated effects of jump and diffusive volatilities are very different. The

jump-driven variance coefficient is 4.25 compared to -1.87 for the diffusive one. Both co-efficients are statistically significant with t-statistics of 7.84 and -4.14, respectively. This implies that the two volatility components affect illiquidity very differently: the jump component positively and the diffusive negatively. These coefficients imply that an increase of one standard deviation in the jump-driven volatility component increases bid-ask spreads by approximately 40 basis points, whereas an equivalent increase in the diffusive volatility component decreases bid-ask spreads by approximately 10 basis points. Firm size maintains a very similar effect compared to those obtained for total volatility. Finally, Fama-MacBeth average $\overline{R}^2$ is 48%, indicating a strong explanatory power for our model.

An alternative yet equivalent way to state our results is that controlling for total volatility, the jump volatility component has a strong positive effect on illiquidity whereas the diffusive component has a negative effect. Although this analysis is exactly equivalent to the one carried out thus far, for convenience and ease of presentation reasons, we report estimation results for the effects jump and diffusive volatility have on illiquidity when controlling for total volatility. These results are presented in the last two columns of Table (3), using Models A and B respectively. The coefficient estimates in Model A and B match their implied values from the coefficient estimates in the original specification.[14]

In summary, our results indicate that the structure of volatility significantly matters for bid-ask spreads beyond raw levels of volatility. While the jump-driven volatility component drives the positive relation between volatility and illiquidity, the diffusive component drives the relation in the opposite direction.

5.4   Information Asymmetry Prediction

In the previous sections we showed that the association between volatility and liquidity is driven almost exclusively by the jump component. Alternatively stated, our results show that the jump source of volatility is associated with liquidity, controlling for total volatility. As discussed in the introduction, because the structure of volatility is governed by the information environment of the firm, this result provides a link between the information environment and liquidity. Nevertheless, prior literature has already established a link between the information environment of the firm and liquidity through information asymmetry. Our predictions suggest that the information environment is likely to create observable differences in liquidity even for firms with identical information asymmetry (or even in the absence of information asymmetry).

---

[14]To see this clearly, define the bid-ask spread as y, jump volatility as x_1, diffusive volatility as x_2, and total volatility as x_3, where $x_3 = x_1 + x_2$. If $y = \alpha x_1 + \beta x_2$ then $y = (\alpha - \beta)x_1 + \beta x_3$ and $y = (\beta - \alpha)x_2 + \alpha x_3$.

We test this predication in two different ways. In the first way, we simply add a control variable to Equation (5) to account for levels information asymmetry. In the second way, we sort our sample into five quintiles of information asymmetry and re-estimate Equation (5) in each quintile. Our empirical proxy for information asymmetry is the probability of informed trade (PIN). PIN is based on the imbalance between buy and sell orders among investors and is therefore technically unrelated to bid-ask spread. The PIN measures are obtained from Stephen Brown's website and are based on Brown and Hillegeist (2007). In their paper they compute PINs using the Venter and De Jong (2006) model to extend the Easley et al. (1997) model.

The results from these tests are presented in Table (4). The first column presents estimation results for Equation (5) when controlling for information asymmetry. The results reveal that although PIN is, as expected, positively associated with bid-ask spreads, all our other results remain qualitatively unchanged (as in Table 3). Columns 2-6 present estimation results for Equation (5) for each information asymmetry quintile from low to high separately. The coefficient for jump volatility is positive with high t-statistics in all quintiles, while the coefficient for diffusive volatility is mostly negative. Taken together, these results suggest that the relation between each source of volatility and liquidity remains unaltered even for firms with similar levels of information asymmetry.[15]

5.5 Turnover Prediction

Higher turnover rates reduce market-makers' inventory costs as they can match the order flow much more easily and consequently increase liquidity (E.g., Tinic and West, 1972; Stoll, 1978a). As discussed earlier in the introduction, diffusive volatility is associated with increased trading, while jump volatility is not (e.g., Giot et al., 2010). This fact entails that the negative association between diffusive volatility and illiquidity is mediated through the effect turnover has on illiquidity. This gives rise to a prediction that diffusive volatility should have no effect on illiquidity after controlling for turnover effects.

To test this prediction we repeat the regressions specified in Equations (4)-(5) this time explicitly accounting for turnover effects by including a turnover variable in these regressions. Table (5) reports estimation results for these regressions. The first column displays the results

---

[15]These tests do not suggest that the structure of volatility does not affect liquidity through information asymmetry as well. Nor do these tests suggest that the information environment does not affect liquidity through information asymmetry. These result simply suggest that the information environment can affect liquidity through its effect on volatility structure independently of the effects the information environment has on liquidity through information asymmetry.

for the effect total variance has on bid-ask spreads. Under this specification, the coefficient estimate for total variance increases to 3.44 with a t-statistic of 6.02 (compared to 2.19 and 5.52 in Table 3, respectively). The turnover coefficient is negative, as expected, consistent with prior studies that argue that higher trading activity decreases illiquidity. The coefficient for total volatility becomes more positive since here we explicitly account for the negative impact turnover has on illiquidity, capturing only the pure relation between total volatility and illiquidity and ignoring its indirect negative effect through turnover.

The second column in Table (5) reports the results for separating between the two volatility components. Under this specification the jump-driven variance coefficient increases to 5.15, while the diffusion-driven variance coefficient dramatically drops to 0.02 (compared to 4.25 and −1.87 in Table 3, respectively). Moreover, the t-statistic for the jump-component coefficient remains high (8.30) but for the diffusive component it drops to 0.04 (compared to 7.84 and −4.14 in Table 3, respectively). The turnover coefficient is negative, similar to that obtained for total volatility. These results confirm that the entire relation between diffusive volatility and illiquidity is indirect and it is completely driven by turnover, as predicted. In contrast, the relation between jump volatility and illiquidity is direct and unrelated to increased trading activity.

5.6   Robustness - Testing for Reverse Causality

By definition, illiquid assets are subject to greater jump risk as thin trading means infrequent transactions where each transaction is more likely to generate large price impacts. Put differently, "technical jumps" can be generated through prices that bounce between bid and ask quotes for wide bid-ask spreads.

To mitigate the concern that this reverse causality drives our results, we test for the effect of increasing the jump volatility component while controlling for turnover rates. By construction, stocks with high turnover rates do not exhibit thin trading. Therefore, we first sort all stocks in each year on turnover rates and form five different portfolios, from low to high. Then, for each portfolio level, we repeat our second method of double sorting on total variance and jump-driven variance and then averaging across all years and all total volatility ranks k. This process is carried out for each of the five turnover portfolios. Therefore we have a five-by-five portfolio ranking sorted on turnover level and jump-driven volatility level. We report the results in Table (6).

Our results show that the dominance of the jump volatility component is maintained in all portfolios: higher jump-driven portfolios always exhibit higher average bid-ask spreads, for

all five turnover portfolios. Formal t-tests for the difference between high and low jump-portfolios all reject the null hypothesis that the corresponding average bid-ask spreads are identical per turnover portfolio, with t-statistics ranging from 8.26–10.76. This suggests that jump volatility plays an important role even for stocks that do not suffer from thin trading.

5.7 Robustness - Crash Risk

We also verified that the dominant effect that the jump component has on illiquidity is not driven by crash risk. In unreported results we find that the dominance of the jump components is qualitatively the same for positive and negative average jump sizes (α). Similarly, when including a dummy variable for negative jumps to control for crash risk, its coefficient estimate is highly nonsignificant. This result is expected and consistent with the way market-makers operate, as they hold non-zero stock inventories in both directions, long and short, exposing them to risks of prices changes in both directions, positive or negative.

6 Volatility Components and Liquidity Risk

A number of studies have shown that liquidity levels are risky (e.g., Pastor and Stambaugh, 2003; Sadka, 2006).[16] Given our findings about the differential effects jump and diffusive volatilities have on liquidity, to the extent that some of this relation is driven by systematic factors, it is possible that these components would play different roles in determining liquidity risk.

Acharya and Pedersen (2005) use a liquidity-adjusted CAPM model to provide a unified framework that accounts for the various effects liquidity risk has on asset prices. In their model, the CAPM "beta" is decomposed into the standard market beta and additional three liquidity-related betas, representing three different channels through which liquidity risk operates: (1) the sensitivity of the stock's illiquidity to the market's illiquidity; (2) the sensitivity of the stock's return to the market's illiquidity; and (3) the sensitivity of the stock's illiquidity to the market's return. Investors demand higher risk premiums for stocks that suffer more in times of stress, times in which they also exhibit large losses in wealth. That is, investors should worry about a security's performance and tradability both in market downturns and when liquidity "dries up".

While Acharya and Pedersen's (2005) model gives clear predictions as to the effects these three sensitivities have on stocks' expected returns, they recognize that they do not explain

---

[16]Amihud and Mendelson (2015) review this literature, see additional references therein.

why different stocks possess those different sensitivity characteristics. Rather, they merely estimate the sensitivities and treat them as given. Our framework allows for a deeper insight into the heterogeneity of these characteristics, which complements their analysis.

The relation between jump volatility and two of the liquidity risk channels described above is straightforward. The first and third channels describe the comovement in individual stock illiquidity with market illiquidity and market returns, respectively, over time. Since we showed that the jump-volatility component is the dominant driver behind illiquidity, it is possible that it would also be the main driver determining its commonality with the other two variables.

The second channel, which describes the comovement between returns and market liquidity, might also be driven by jump risk. Firms with higher jump risk are more likely to experience large losses (i.e., a negative jump) when markets "dry up" for lack of funding, thus increasing the commonality between returns and market liquidity. Furthermore, trading costs for individual stocks might also increase in an illiquid environment and thus put downward pressure on prices. Since liquidity costs are driven by jump risk, it is possible that these firms with higher jump risk that are more likely to experience price declines in illiquid markets.

To test these possibilities we follow Acharya and Pedersen (2005) and construct equivalent measures for the three liquidity-related betas. If indeed jump-risk is the dominant driver behind illiquidity, it is possible that higher values for all three liquidity-related betas are correlated with higher measures for jump-risk. In contrast, diffusive-risk should be less correlated with these betas.

Specifically, let β^{1L}, β^{2L} and β^{3L} denote the three liquidity related betas, respectively. Following Acharya and Pedersen (2005), we define

$$\beta_{i,t}^{1L} = cov\left(L_t^i, L_t^M\right) \qquad \beta_{i,t}^{2L} = cov\left(r_t^i, L_t^M\right) \qquad \beta_{i,t}^{3L} = cov\left(L_t^i, r_t^M\right) \tag{6}$$

where L_t^i and L_t^M are liquidity measures for stock i and for the aggregate market M. Similarly, r_t^i and r_t^M are stock i returns and market returns, respectively.

To estimate these β's we used the Sadka (2006) variable-permanent liquidity factor as our measure for aggregate market liquidity, which is the one associated with information driven price changes. For individual stock liquidity measures we used the (negative) value of monthly average TAQ bid-ask spreads per stock.[17] All monthly return data and aggre-

---

[17]We used the negative values of bid-ask spreads to convert them from a measures of illiquidity (costs) to a measure of liquidity, to be consistent with the Sadka (2006) framework and liquidity factors.

gate market return data were obtained from CRSP. As in Acharya and Pedersen (2005) we expect all three betas to be positive, that is, the higher the beta the larger liquidity risk is.

For each month between 2002-2011 we used a 60-month rolling window to estimate the three covariances (betas) per stock i as in Equations (6).[18] Then, for each beta we ran a Fama-MacBeth regression on our two measures of jump and diffusive volatility, $V_{i,t}^d$ and $V_{i,t}^j$. That is,

$$\beta_{i,t}^k = \alpha + \gamma_1 V_{i,t}^d + \gamma_2 V_{i,t}^j + \gamma_3 \ln(size_{i,t}) + \varepsilon_{i,t} \qquad (7)$$

where, k is $1L$, $2L$ or $3L$. We also included (the log of) the firm's market capitalization as a control variable. We report our results in Table (7).

As seen in Table (7), the jump volatility component has a positive and statistically significant effect for all three betas. On the other hand the diffusive component has a (non-significant) negative effect. That is, only jump volatility increases liquidity risk while diffusive volatility does not.

Furthermore, to enhance our analysis we followed Pastor and Stambaugh (2003) to take a deeper look into the factors determining $\beta_{i,t}^{2L}$, which measures the relation between returns and market liquidity. They first obtained β^{2L} using a richer specification based on a three factor Fama-French (FF) model. Specifically,

$$r_{i,t} = \beta_i^0 + \beta_i^M MKT_t + \beta_i^S SMB_t + \beta_i^H HML + \beta^{2L} L_t^M + \varepsilon_{i,t} \qquad (8)$$

where MKT_t, SMB_t and HML_t are the regular FF factors (market, small minus big, and high minus low, respectively) and L_t^M is the aggregate liquidity factor. Therefore, β^{2L} is the coefficient for the aggregate liquidity factor. They also assumed that $\beta_{i,t}^{2L}$ has the following linear form,

$$\beta_{i,t}^{2L} = \psi_{1,i} + \psi_{2,i}' \mathbb{Z}_{i,t-1} \qquad (9)$$

where $\mathbb{Z}_{i,t-1}$ is a vector of characteristic variables that affect $\beta_{i,t}^{2L}$. Therefore, Equation (8) can be rephrased as,

$$r_{i,t} = \beta_i^0 + \beta_i^M MKT_t + \beta_i^S SMB_t + \beta_i^H HML + \left(\psi_{1,i} + \psi_{2,i}' \mathbb{Z}_{i,t-1} \right) L_t^M + \varepsilon_{i,t} \; ,$$

from which we can define the following residual,

$$e_{i,t} = r_{i,t} - \beta_i^M MKT_t - \beta_i^S SMB_t - \beta_i^H HML$$

---

[18]In practice, instead of using simple covariances we used OLS regressions to estimate these three β's, where each β was obtained as the estimated coefficient.

that can be expressed as,

$$e_{i,t} = \psi_0 + \psi_1 L_t^M + \psi_2' \mathbb{Z}_{i,t-1} L_t^M + v_{i,t} \ . \tag{10}$$

Namely, $e_{i,t}$ is the share of returns that remains unexplained by all regular factors and is affected only by liquidity.

Estimating ψ_2' allows for gauging the contribution each characteristic in $\mathbb{Z}$ has on liquidity risk, β^{2L}, as defined in Equation (9). In the context of our analysis, we used jump volatility and diffusive volatility as two characteristics in $\mathbb{Z}$ and our goal is to measure how each characteristic affects $\beta_{i,t}^{2L}$.

We report our regression results for Equation (10) in Table (8), where estimates for ψ_1 and ψ_2' are reported separately. Focusing on the vector of coefficients ψ_2' it can be seen that jump and diffusive volatilities have very different effects. The interactions between the jump component and both Sadka (2006) liquidity factors have positive and statistically significant coefficients. On the other hand, the interactions between the diffusive component and the liquidity factors are non-significant. That is, this richer framework for the liquidity measure also supports the unique role jump volatility plays: given the structure of $\beta_{i,t}^{2L}$ specified in Equation (9), only the jump volatility component increases liquidity risk.

In summary, these findings provide further support for the dominant role jump volatility plays in the relation between volatility and liquidity. Not only liquidity levels are driven by the jump component but liquidity risk as well. We do not find a similar significant effect for the diffusive component. Finally, this pattern exists in all three channels through which liquidity risk operates.

7   Conclusions

In our analysis, we delve a deeper look into the different factors determining the relation between total volatility and illiquidity. Disentangling total volatility into its diffusive and jump components reveals a more complex picture. We find that it is jump volatility that drives the positive relationship, while diffusive volatility has a negative contribution. These results are maintained at any level of information asymmetry.

Finally, we also find that the differential effects each volatility component has on illiquidity carry on in the same structural fashion into additional dimensions of illiquidity. That is, each volatility component maintains its type of impact on liquidity risk and liquidity risk premiums.

These findings contribute to several different strands of the academic literature. They further expand our understanding of the determinants of liquidity, particularly in relation to the role volatility plays, and of the way firms' information environment affects capital markets. Moreover, they enhance our understanding of the mechanisms that drive liquidity risk and liquidity risk premiums. Finally, they shed light on a set of new consequences that jumps create, in addition to a number of previously documented ones, such as their consequences to credit risk, market beta, and stock option pricing.

At the regulatory level, our study provides evidence that implementing accounting policies that encourage more continuous flow of information and disclosure may make sense in order to increase liquidity. Such policies are likely to improve the diffusive component of volatility, smooth potential surprises, and thus improve liquidity.

We note that causal terms we used to describe the mechanism through which the volatility components affect liquidity are purely inspired by the theoretical arguments that motivated our empirical study. In this study we aimed towards the more modest goal, to be the first documenting associations that are consistent with these theoretical predictions.

Last, we realize that we do not offer an explicit theoretical model to gauge the different effects that jump and diffusive volatilities have on liquidity. Nevertheless, the theoretical paradigms mentioned in the introduction provide the inspiration for our empirical investigation, which is significant in itself, particularly given the fact that so far no work has been done on the topic. Therefore, our findings provide the motivation for further developments of an explicit theoretical model, which is left for future research.

Appendix A: Jumps and the Information Environment

Information proxy	Coefficient	Info Asymmetry (B/A spread)	Firm & Year fixed effects	N
		Panel A		
Number of analysts	-0.042	-	Yes	55,558
	(-20.23)	-		
Management forecast (*Yes/No*)	−0.178	-	Yes	55,558
	(-9.50)	-		
Number of management forecasts	-0.023	-	Yes	55,558
	(-8.98)	-		
Drop in analyst coverage due to	0.039	-	Yes	55,558
closure of brokerage house	*(3.93)*	-		
		Panel B		
Number of analysts	-0.029	17.03	Yes	55,558
	(-14.18)	*(51.48)*		
Management forecast (*Yes/No*)	−0.181	17.62	Yes	55,558
	(-9.94)	*(53.65)*		
Number of management forecasts	-0.023	17.63	Yes	55,558
	(-9.53)	*(53.67)*		
Drop in analyst coverage due to	0.063	17.68	Yes	55,558
closure of brokerage house	*(5.35)*	*(53.75)*		

In this appendix we replicate in our sample period (2002-2011) the results obtained in our companion study. Panel A of the table above presents regression results for jump volatility on various proxies for information environment and time and firm fixed effects, without controlling for information asymmetry. The number of analysts covering the firm, the fact

that management provides guidance, and the number of management guidance by the firm, are all negatively associated with the jump component of total volatility (coefficients of -0.042, -0.178 and -0.023 respectively). t-statistics are reported in parentheses. Similarly, we use a drop in analyst coverage as a result of brokerage house closure as another proxy for information environment. Based on a difference-in-differences design with time and firm fixed effects we find that a drop in coverage casually increases jump volatility in the year of the change compared to unaffected years and firms (coefficient of 0.039).

In Panel B we repeat all our tests this time including another variable, bid-ask spreads, to control for asymmetric information. All our results remain unaltered even after controlling for information asymmetry effects.

Taken together, and as suggested by our companion study, these results provide confirmation that the information environment determines the composition of volatility.

Appendix B: Model and Estimation Method

Following Merton (1976), let S_t denote a stock price at time t on a filtered probability space $(\Omega, F, (F_t), P)$, which is assumed to satisfy the following stochastic differential equation:

$$\frac{dS_t}{S_t} = (\mu - \lambda \cdot E(Z-1)) dt + \sigma dW_t + (Z-1) dN_t,$$

where μ and σ^2 denote the instantaneous mean and variance of the stock return in the absence of jumps, and W_t is a Wiener process. Furthermore, N_t is a Poisson process with intensity $\lambda > 0$, and Z is the log-normal jump amplitude with $\ln Z \backsim N(\alpha; \gamma^2)$ such that

$$E(Z-1) = \exp(\alpha + \frac{\gamma^2}{2}) - 1.$$

We postulate that W_t, N_t, and Z_t are mutually independent. The parameter vector θ is $\theta = (\mu, \sigma^2, \lambda, \alpha, \gamma^2)'$, where α and γ^2 represent the mean and variance of the jump size of stock returns.

Since the Brownian motion and the Poisson process of jump events are independent, the total return variance can be decomposed into

$$V \equiv Var\left(\frac{S_t}{S_0}\right) = Var(\sigma W_t) + Var(J_t), \tag{11}$$

which is the sum of the diffusion-related variance and the jump-related variance. We denote

$$
\begin{aligned}
V^d &\equiv Var(\sigma W_t) \\
V^j &\equiv Var(J_t)
\end{aligned}
$$

as the respective variances. Furthermore, following Merton (1976) and Navas (2003), these variances can be expressed in terms of the respective basic process parameters as

$$
\begin{aligned}
V^d &= \sigma^2 t \\
V^j &= \lambda(\alpha^2 + \gamma^2) t,
\end{aligned}
\tag{12}
$$

which allow for easily calculating these values based on the parameter vector θ.

Following Ait-Sahalia (2004), under the assumptions specified above, the transition density $f_{\Delta \ln S}$ of $\ln S_t$ can be expressed by

$$f_{\Delta \ln S}(x; \theta) = (1 - \lambda \cdot \Delta t) \cdot f_{\Delta \ln S|\Delta N_t=0}(x|\Delta N_t = 0; \theta) + \lambda \cdot \Delta t \cdot f_{\Delta \ln S|\Delta N_t=1}(x|\Delta N_t = 1; \theta),$$

where $f_{\Delta \ln S | \Delta N_t=0}$ and $f_{\Delta \ln S | \Delta N_t=1}$ represent the transition densities of $\ln S_t$, conditioning on $\Delta N_t = 0$ and $\Delta N_t = 1$ jumps between two sampling points, respectively, and $\Delta t > 0$ denotes the time distance between sampling points. Since

$$
\begin{aligned}
P(\Delta N_t &= 0) = 1 - \lambda \cdot \Delta t + o(\Delta t) \\
P(\Delta N_t &= 1) = \lambda \cdot \Delta t + o(\Delta t) \\
P(\Delta N_t &> 0) = o(\Delta t),
\end{aligned}
$$

additional jumps between two sampling points are neglected. Closed form expressions for the conditional densities are given by

$$
f_{\Delta \ln S | \Delta N=k}(x | \Delta N_t = k; \theta) = \frac{1}{\sqrt{2 \cdot \pi \cdot v(k)}} \cdot \exp\left(-\frac{(x - m(k))^2}{2 \cdot v(k)}\right),
$$

where

$$
\begin{aligned}
m(k) &= \left(\mu - \sigma^2/2 - \lambda \cdot E(Z-1)\right) \cdot \Delta t + k \cdot a \\
v(k) &= \sigma^2 \cdot \Delta t + k \cdot \gamma^2,
\end{aligned}
$$

with $k \in \{0, 1\}$. Based on a sample of n stock returns $\Delta \ln s_1, ..., \Delta \ln s_n$, the resulting likelihood estimate $\widehat{\theta}$ of θ is computed numerically as

$$
\hat{\theta} = \arg\max_{\theta} \left(\sum_{i=1}^{n} \ln f_{\Delta \ln S}(\Delta \ln s_i; \theta)\right).
$$

Appendix C: Variable Description

1. μ - Constant parameter of the diffusion process representing the diffusive drift.

2. σ - Constant parameter of the diffusion process representing the diffusive volatility.

3. λ - Constant parameter of the compound jump process representing the average number of jumps per annum (year).

4. α - Constant parameter of the compound jump process representing the average jump size.

5. γ - Constant parameter of the compound jump process representing the standard deviation of the jump size α.

6. **Bid-Ask Spread** ($Liq_{i,t}$) - Annual average bid-ask spread for firm i across all intraday quotes based on available TAQ data.

7. **Total Var** - Annual total return variance for stock i in year t, $V_{i,t}$; see Equation (7).

8. **Diffusive Var** - The diffusive component of annual total return variance for stock i in year t, $V_{i,t}^d$; see Equation (8).

9. **Jump Var** - The jump component of annual total return variance for stock i in year t, $V_{i,t}^j$; see Equation (8).

10. **Turnover** - The average ratio of daily volume to shares-outstanding for firm i in year t.

11. $ln(\textbf{size})$ - The natural log of firm i's market capitalization in year t.

References

Acharya, D., Pedersen, L.H. 2005. Asset Pricing with Liquidity Risk. *Journal of Financial Economics* 66, 341–360.

Ait-Sahalia, Y. 2004. Disentangling Diffusion from Jumps. *Journal of Financial Economics* 74, 487–528.

Ait-Sahalia, Y., Karaman, M., Mancini, L. 2015. The Term Structure of Variance Swaps and Risk Premia. Working Paper.

Amihud, Y. 2002. Illiquidity and stock returns: Cross-section and time series effects. *Journal of Financial Markets* 5, 31–56.

Amihud, Y., Mendelson H. 1980. Dealership Market: Market-Making with Inventory. *Journal of Financial Economics*, 8, 31–53.

Amihud, Y., Mendelson, H. 1989. The Effects of Beta, Bid-Ask Spread, Residual Risk, and Size on Stock Returns. *The Journal of Finance*, Vol. 44 (2), 479–486.

Amihud, Y., Mendelson, H. 2015. The Pricing of Illiquidity as a Characteristic and as Risk. *Multinational Finance Journal*, 19 (3), 149–168.

Amir, E., Levi, S. 2016. The Precision of Information in Stock Prices, and Its Relation to Disclosure, Liquidity, and Cost of Equity. *Working paper*.

Banerjee, S., Gatchev, V. A., Spindt, P. A. 2007. Stock Market Liquidity and Firm Dividend Policy. *Journal of Financial and Quantitative Analysis,* 42 (2), 369-397.

Bao, J., Pan, J., Wang, J. 2013. Bond Illiquidity and Excess Volatility. *Review of Financial Studies*, 26 (12), 3068–3103.

Benston, G. J., Hagerman, R. L. 1974. Determinants of the Bid-Ask Spread in the Over-the-Counter Market. *Journal of Financial Economics*, 1, 353–364.

Balakrishnan, K., Billings, M. B. , Kelly, B., Ljungqvist, A. 2014. Shaping Liquidity: On the Causal Effects of Voluntary Disclosure. *The Journal of Finance*, 69 (5), 2237-2278.

Bhide, A. 1993. The Hidden Costs of Stock Market Liquidity. *Journal of Financial Economics,* 34 (1), 31-51.

Bollerslev, T., Todorov, V. 2011. Tails, Fears, and Risk Premia. *The Journal of Finance,* 66 (6), 2165–2211.

Bollerslev, T., Li, S. Z., Todorov, V. 2016. Roughing Up Beta: Continuous Versus Discontinuous Betas and the Cross Section of Expected Stock Returns. *Journal of Financial Economics,* 120 (3), 464–490.

Bollerslev, T., Todorov, V., Xu, L. 2015. Tail Risk Premia and Return Predictability. *Journal of Financial Economics*, forthcoming.

Brunnermeier, M.K., Pedersen, L.H. 2009. Market Liquidity and Funding Liquidity. *Review of Financial Studies* 22 (6), 2201–2238.

Chen, H., Joslin, S., Ni, S. 2014. Demand for Crash Insurance, Intermediary Constraints, and Risk Premia in Financial Markets. Working Paper.

Cont, R., Tankov, P. 2003. *Financial Modelling With Jump Processes*, Chapman and Hall, CRC Financial Mathematics Series, London.

Copeland, T.E., Galai, D. 1983. Information Effects on the Bid-Ask Spread. *The Journal of Finance*, 38, 1457–1469.

Cremers K. J. M., Driessen J., Maenhout P. 2008. Explaining the Level of Credit Spreads: Option-Implied Jump Risk Premia in a Firm Value Model. *Review of Financial Studies*, 21 (5), 2209-2242.

Cremers K. J. M., Halling, M., Weinbaum, D. 2015. Aggregate Jump and Volatility Risk in the Cross-Section of Stock Returns. *The Journal of Finance*, 70 (2), 577–614.

Duffie D., Pan J., and Singleton K. 2000. Transform Analysis and Asset Pricing for Affine Jump-diffusions. *Econometrica*, 68 (6), 1343–1376.

Froot, K. A., Stein, J. C. 1998. Risk Management, Capital Budgeting, and Capital Structure Policy for Financial Institutions: an Integrated Approach. *Journal of Financial Economics*, 47, 55–82.

Garleanu, H., Pedersen, L. H., Poteshman, A. M. 2009. Demand-Based Option Pricing. *Review of Financial Studies*, 22 (10), 4259–4299.

Giot, P., Laurent, S., Petitjean, M. 2010. Trading activity, realized volatility and jumps. *Journal of Empirical Finance,* 17 (1), 168–175.

Glosten, L. R., Milgrom, P. R. 1985. Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders. *Journal of Financial Economics*, 14, 71–100.

Gromb, D., Vayanos, D. 2002. Equilibrium and Welfare in Markets with Financially Constrained Arbitrageurs. *Journal of Financial Economics,* 66, 361–407.

Ho, T., Stoll, H.R. 1981. Optimal Dealer Pricing Under Transactions and Return Uncertainty. *Journal of Financial Economics*, 9, 47–73.

Ho, T., Stoll, H.R. 1983. The Dynamics of Dealer Markets Under Competition. *The Journal of Finance*, 38 (4), 1053–1074.

Jameson, M., Wilhelm, W. 1992. Market Making in the Options Markets and the Costs of Discrete Hedge Rebalancing. *The Journal of Finance*, 47 (2), 765–779.

Kelly, B., Ljungqvist, A. 2012. Testing Asymmetric-Information Asset Pricing Models. *Review of Financial Studies,* 25 (5), 1366-1413.

Kyle, A. S. 1985. Continuous Auctions and Insider Trading. *Econometrica,* 53, 1315–1335.

Lee, S. S., Mykland, P. A., 2008. Jumps in Financial Markets: A New Nonparametric Test and Jump Dynamics. *Review of Financial Studies*, 21(6), 2535-2563.

Lipson, M. L., Mortal, S. 2009. Liquidity and capital structure, *Journal of Financial Markets*, 12 (4), 611-644.

Longstaff, F. A. 1995. How Much Can Marketability Affect Security Values? *The Journal of Finance*, 50, 1767–1774.

Longstaff, F. A. 2014. Valuing Thinly Traded Assets. *NBER Working Paper Series*, 20589.

Maheu, J. M., McCurdy, T. H. 2004. News Arrival, Jump Dynamics, and Volatility Components for Individual Stock Returns. *The Journal of Finance*, 59 (2), 755-793.

Merton, R. C. 1976. Option Pricing when the Underlying Stock Returns are Discontinuous. *Journal of Financial Economics*, 3, 125–144.

Naik, N. Y., Yadav, P.K. 2003a. Do Dealer Firms Manage Inventory on a Stock-by-Stock or a Portfolio Basis. *Journal of Financial Economics*, 69, 325–353.

Naik, N. Y., Yadav, P.K. 2003b. Risk Management with Derivatives by Dealers and Market Quality in Government Bond Markets. *The Journal of Finance*, 58 (5), 1873–1904.

Navas, J. F. 2003. Correct Calculation of Volatility in a Jump-Diffusion Model. *The Journal of Derivatives*, Winter 2003, 11 (2), 66–72.

Pan, J. 2002. The Jump-Risk Premia Implicit in Options: Evidence from an Integrated Time-Series Study. *Journal of Financial Economics*, 63, 3–50.

Pastor, L., Stambaugh, R.F. 2003. Liquidity Risk and Expected Stock Returns. *Journal of Political Economy*, 111, 642–685.

Rüschendorf, L., Woerner, J.H. 2002. Expansion of transition distributions of Levy processes in small time. *Bernoulli*, 8, pp. 81–96.

Sadka, R. 2006. Momentum and Post-Earnings-Announcement Drift Anomalies: The Role of Liquidity Risk. *Journal of Financial Economics*, 80, 309–349.

Stoll, H.R. 1978a. The Supply of Dealer Services in Securities Markets. *The Journal of Finance*, 34 (4), 1133–1151.

Stoll, H.R. 1978b. The Pricing of Security Dealer Services: An Empirical Study of NASDAQ Stocks. *The Journal of Finance*, 33 (4), 1153–1172.

Stoll, H.R. 2000. Friction. *The Journal of Finance*, 55 (4), 1479–1514.

Tauchen, G., Zhoub, H. 2011. Realized Jumps on Financial Markets and Predicting Credit Spreads. *Journal of Econometrics,* 160, 102–118.

Tinic, S. M., West R. R. 1972. Competition and the Pricing of Dealer Service in the Over-the-Counter Stock Market. *The Journal of Financial and Quantitative Analysis*, 7(3), 1707-1727.

Todorov, V. 2010. Variance Risk-Premium Dynamics: The Role of Jumps. *Review of Financial Studies*, 23 (1), 345–383.

Todorov, V., Bollerslev, T. 2010. Jumps and Betas: A New Framework for Disentangling and Estimating Systematic Risks. *Journal of Econometrics,* 157. 220-235.

Yan, S. 2011. Jump Risk, Stock Returns, and Slope of Implied Volatility Smile, *Journal of Financial Economics*, 99, 216-233.

Yu, J. 2007. Closed-Form Likelihood Approximation and Estimation of Jump-Diffusions with an Application to the Realignment Risk of the Chinese Yuan. *Journal of Econometrics*, 141, 1245–1280.

Zhou, C. 2001. The Term Structure of Credit Risk with Jump Risk. *Journal of Banking and Finance*, 25, 2015–2040.

Figure 1

BID-ASK SPREADS AND VOLATILITY COMPONENTS: SORTED PORTFOLIOS

This figure is a graphic presentation of Table (2). Panels A and B plot average bid-ask spreads per volatility level. Each graph in panel A controls for a jump volatility level, and each graph in Panel B controls for a diffusive volatility level.

Panel A: Diffusive Volatility Levels
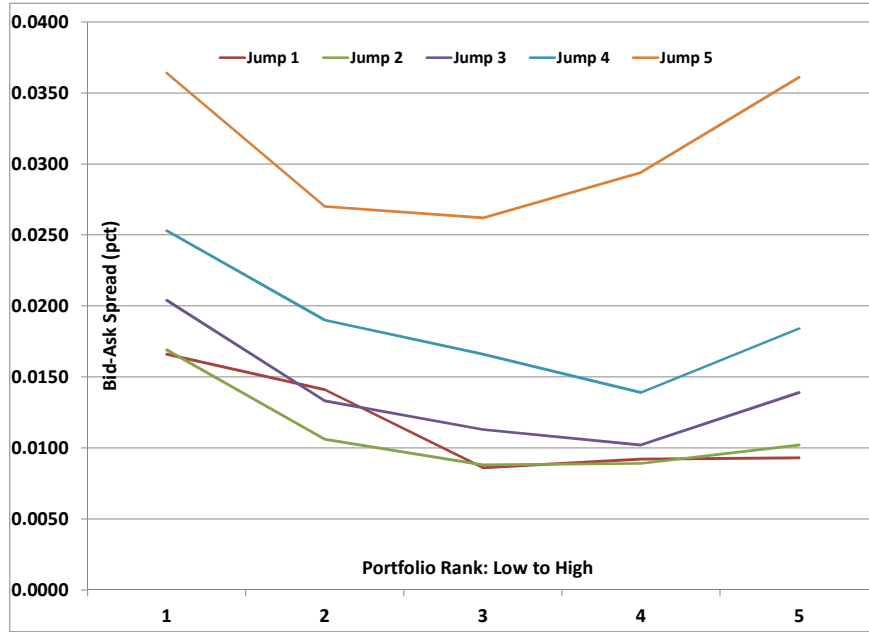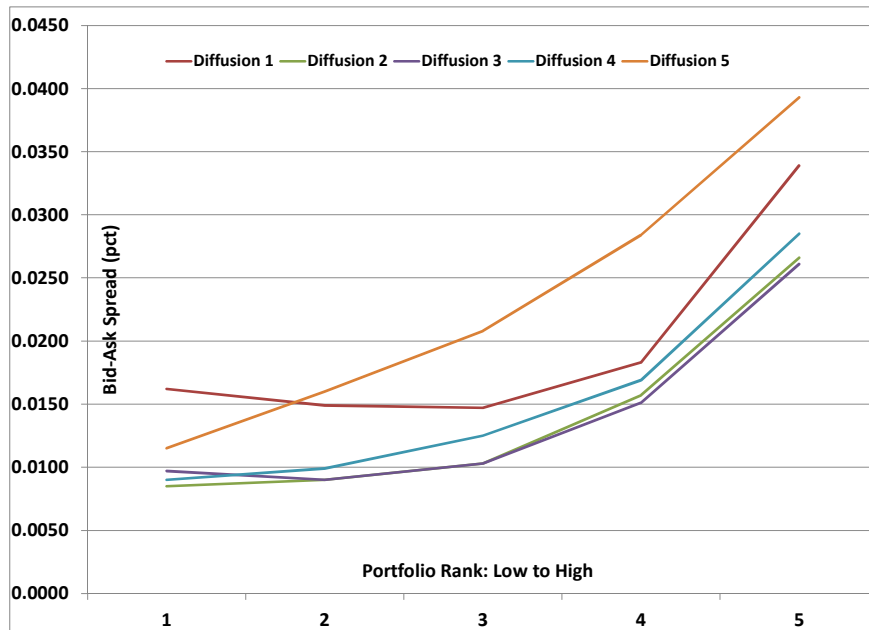

Panel B: Jump Volatility Levels

Table 1: **DESCRIPTIVE STATISTICS.** This table reports descriptive statistics for our basic variables. Panel A reports average estimates for total, jump, and diffusive daily standard deviations as defined in Equations (2) and (3). Panel B reports average annual bid-ask spreads. Averages are calculated across all years and stocks in our sample. For total standard deviations of returns, we used realized standard deviations, while for the diffusive and jump components we used model implied volatilities. The number of observations in our sample is 55,558. See Appendix B for variable description.

	Mean	S.D.	Min	.25	Mdn	.75	Max
Panel A: Daily Return Volatility (Std)							
Total	.0292	.0168	.0050	.0169	.0255	.0376	.1129
Diffusion	.0186	.0100	0	.0111	.0170	.0243	.0591
Jump	.0203	.0159	0	.0090	.0173	.0286	.1067
Panel B: Liquidity Costs							
Bid-Ask Spread	.0187	.0252	.0003	.0030	.0085	.0235	.2525

Table 2: **UNIVARIATE ANALYSIS: SORTED PORTFOLIOS.** We sorted all stocks per year on one volatility component and then sorted again on the other component. In Panel A, we first sorted on diffusive volatility and formed $d = 1, ..., 5$ portfolios. Then, each diffusive portfolio d was sorted again on the jump volatility component, to form additional five portfolios. This allows for testing the marginal effect of increasing total volatility by increasing the jump volatility alone, while controlling for the diffusive component. In Panel B, we first sorted on jump volatility and then on diffusive volatility to test the marginal effect of diffusive volatility while controlling for jump volatility. Averages in each prtfoilio represent average bid-ask spreads in period $t + 1$. We also report the differences in bid-ask spreads between the highest and lowest portfolios and their $t-$statistics.

Portfolio	Low	2	3	4	High
Panel A: Controlling for Diffusion					
Low Jump	.0162	.0085	.0097	.0090	.0115
2	.0149	.0090	.0090	.0099	.0160
3	.0147	.0103	.0103	.0125	.0208
4	.0183	.0157	.0151	.0169	.0284
High Jump	.0339	.0266	.0261	.0285	.0393
High-Low	*.0176*	*.0181*	*.0164*	*.0194*	*.0278*
t-stat	*18.94*	*22.90*	*20.86*	*24.80*	*27.57*
Panel B: Controlling for Jumps					
Low Diffusive	.0166	.0169	.0204	.0253	.0364
2	.0141	.0106	.0133	.0190	.0270
3	.0086	.0088	.0113	.0166	.0262
4	.0092	.0089	.0102	.0139	.0294
High Diffusive	.0093	.0102	.0139	.0184	.0361
High-Low	*-.0073*	*-.0067*	*-.0065*	*-.0068*	*-.0003*
t-stat	*-13.10*	*-10.95*	*-8.42*	*-7.76*	*-0.20*

Table 3: **FAMA MAC-BETH REGRESSION RESULTS: VOLATILITY AND ILLIQUIDITY.**
This table reports Fama-MacBeth regression results for total volatility and for the marginal effects each volatility component have on bid-ask spreads, as specified in Equations (4)-(5). The first column corresponds to Equation (4): $Liq_{i,t+1} = \beta_0 + \beta_1 V_{1,t} + \beta_2 ln(size_{i,t}) + \epsilon_{i.t}$ and estimates the effect total volatility has on bid-ask spreads. The second column corresponds to Equationn (5): $Liq_{i,t+1} = \beta_0 + \beta_1 V_{1,t}^d + \beta_2 V_{1,t}^j + \beta_3 ln(size_{i,t}) + \epsilon_{i.t}$ and estimates the effect each volatility component has on bid-ask spreads. Model A and B are additional versions of Equation (5) as discussed in Section 5.3. $t-$statistics are reported in parentheses, and *** denotes 1% statistical significance. See Appendix C for variable description.

Variable	Total Volatility	Volatility Components	Model A	Model B
Diffusive-var	-	-1.8707***	-	-6.12***
	-	(-4.14)	-	(-9.25)
Jump-var	-	4.2548***	6.12***	-
	-	(7.84)	(9.25)	-
Total-var	2.1974***	-	-1.87***	4.25***
	(5.52)	-	(-4.14)	(7.84)
ln(size)	-0.0082***	-0.0081***	-0.01***	-0.01***
	(-10.09)	(-9.86)	(-9.86)	(-9.86)
Constant	0.1209***	0.1196***	0.11***	0.11***
	(10.90)	(10.70)	(10.70)	(10.70)
Average-$\overline{R}^2$	48%	48%	48%	48%
Observations	44,171	44,171	44,171	44,171

32

Table 4: **INFORMATION ASYMMETRY PREDICTION.** This table reports estimation results for Equation (5) when controlling for asymmetric information. Our proxy for information asymmetry is the probability of informed trade (PIN). PIN is based on the imbalance between buy and sell orders among investors. These measures are obtained from Stephen Brown's website and are based on Brown and Hillegeist (2007). The results in the first column are based on $Liq_{i,t+1} = \beta_0 + \beta_1 V_{1,t}^d + \beta_2 V_{1,t}^j + \beta_3 ln(size_{i,t}) + \beta_4 PIN_{i,t} + \epsilon_{i,t}$, when regressing this model on all firm years in our data. Columns 2-6 report estimation results for $Liq_{i,t+1} = \beta_0 + \beta_1 V_{1,t}^d + \beta_2 V_{1,t}^j + \beta_3 ln(size_{i,t}) + \epsilon_{i,t}$ applied to each information asymmetry quintile separately from low to high. $t-$statistics are reported in parentheses, and *** denotes 1% statistical significance. For further details see Section 5.4.

PIN Rank	All	Low	2	3	4	High
Jump var	4.367***	6.646***	3.386***	2.323***	3.044***	6.303***
	(5.91)	(4.16)	(4.42)	(5.58)	(7.11)	(5.96)
Diffusive var	-0.748	0.593	-1.005	-0.635	-1.286***	3.867
	(-0.80)	(0.58)	(-1.22)	(-0.69)	(-2.42)	(1.71)
ln(size)	-0.007***	-0.007***	-0.005***	-0.004***	-0.004***	-0.010***
	(-10.91)	(-12.65)	(-12.75)	(-10.06)	(-13.79)	(-8.58)
PIN	0.023***	-	-	-	-	-
	(10.35)	-	-	-	-	-
Constant	0.092***	0.112***	0.075***	0.071***	0.070***	0.149***
	(10.65)	(12.23)	(12.73)	(10.43)	(14.41)	(8.93)
Average-$\overline{R}^2$	0.52	0.52	0.47	0.45	0.46	0.49
Observations	38,355	7,675	7,672	7,670	7,672	7,666

Table 5: **TURNOVER PREDICTION.** This table reports Fama-MacBeth regression results for total volatility and for the marginal effects each volatility component have on bid-ask spreads, this time controlling for turnover effects. That is, the first column corresponds to Equation (4): $Liq_{i,t+1} = \beta_0 + \beta_1 V_{1,t} + \beta_2 ln(size_{i,t}) + \beta_3 turnover_{i,t} + \epsilon_{i,t}$ and estimates the effect total volatility has on bid-ask spreads after controlling for turnover effects. The second column corresponds to Equationn (5): $Liq_{i,t+1} = \beta_0 + \beta_1 V_{1,t}^d + \beta_2 V_{1,t}^j + \beta_3 ln(size_{i,t}) + \beta_4 turnover_{i,t} + \epsilon_{i,t}$ and estimates the effect each volatility component has on bid-ask spreads after controlling for turnover. $t-$statistics are reported in parentheses, and *** denotes 1% statistical significance. See Appendix C for variable description.

Variable	Total Volatility	Volatility Components
Diffusive-var	-	0.0225
	-	(0.04)
Jump-var	-	5.1547***
	-	(8.30)
Total-var	3.4452***	-
	(6.02)	-
ln(size)	-0.0076***	-0.0075***
	(-11.93)	(-11.55)
Turnover	-0.0015***	-0.0015***
	(-5.50)	(-5.44)
Constant	0.1145***	0.1136***
	(12.90)	(12.57)
Average-$\overline{R}^2$	50%	50%
Observations	44,171	44,171

Table 6: **BID-ASK SPREADS AND RELATIVE SHARE OF JUMP COMPONENT: BY TURNOVER RATE.** We first sorted all stocks in each year into five different portfolios, from low to high. Then, for each portfolio level, we repeated our second method of double sorting on total variance and jump-driven variance and then averaging across all years and all total volatility ranks k per jump rank. This process was carried out for each of the five turnover portfolios separately. Then, for each jump portfolio level and turnover level, we calculated average bid-ask spreads in period $t + 1$. We also report the differences in bid-ask spreads between the highest and lowest portfolios and their $t-$statistics.

Jump	Low	2	3	4	High	*High-Low*	*t*-stat
Low Turnover	.0354	.0384	.0389	.0424	.0479	*.0125*	*10.73*
2	.0174	.0201	.0213	.0227	.0248	*.0074*	*10.08*
3	.0083	.0103	.0107	.0126	.0151	*.0068*	*13.19*
4	.0050	.0058	.0059	.0071	.0088	*.0038*	*10.76*
High Turnover	.0040	.0044	.0044	.0052	.0066	*.0026*	*8.26*

Table 7: **LIQUIDITY RISK** – β^{1L}, β^{2L} **AND** β^{3L}. This table reports regression results for Equation (8): $\beta_{i,t}^{k} = \alpha + \gamma_1 V_{i,t}^d + \gamma_2 V_{i,t}^j + \gamma_3 ln(size_{i,t}) + \epsilon_{i,t}$, where $k = 1L, 2L, 3L$. This equation measures the effects jump and diffusive volatility have on β^{1L}, β^{2L} and β^{3L}, when they are all obtained from a simple covariances measure as specified in Equation 6. t−statistics are reported in parentheses, and *** denotes 1% statistical significance.

	$\beta^{1L} = Cov\left(L^i, L^M\right)$	$\beta^{2L} = Cov\left(R^i, L^M\right)$	$\beta^{3L} = Cov\left(L^i, R^M\right)$
Duffusive Var	-26.546***	-537.760***	-0.262
	(-4.65)	(-5.11)	(-0.22)
Jump Var	61.460***	93.824***	5.914***
	(9.13)	(2.27)	(7.74)
ln(size)	-0.090***	-0.063***	-0.005***
	(-14.32)	(-7.11)	(-6.18)
Constant	1.564***	1.305***	0.080***
	(14.05)	(10.81)	(6.60)

Table 8: **CHARACTERISTICS OF β^{2L}.** This table reports regression results for ψ_2' in Equation (10): $e_{i,t} = \psi_0 + \psi_1 L_t^M + \psi_2' \mathbb{Z}_{i,t-1} L_t^M + v_{i,t}$, which in return determines β^{2L} in Equation (9): $\beta_{i,t}^{2L} = \psi_1 + \psi_2' \mathbb{Z}_{i,t-1}$. Following Pastor and Stambaugh (2003) this specification determines the effect different chracteristics in $\mathbb{Z}_{i,t-1}$ have on the sensitivity of stock returns to market liquidity, $\beta_{i,t}^{2L}$. For market liquidity factors we use the Sadka (2006) Variable-Permanent and Fixed-Transitory factors. $t-$statistics are reported in parentheses, and 1% and 10% statistical significance levels are denoted by *** and *, respectively. For more details see Equation (10).

Characteristic	Coefficient
Vector ψ_1 :	
Variable-Permanent Liquidity Factor	0.14***
	(4.24)
Fixed-Transitory Liquidity Factor	5.12***
	(9.84)
Vector ψ_2' :	
Jump×Variable Factor	81.61***
	(3.26)
Jump×Fixed Factor	9348.29***
	(29.47)
Diffusion×Variable Factor	-112.06*
	(-1.84)
Diffusion×Fixed Factor	1229.87
	(1.57)
Constant	0.00***
	(2.09)